





Cut



Excellent + Very Good.

These diamonds will have a high degree of brilliance, fire and scintillation.



Good

This grade will generally be a bit darker or lacking scintillation.



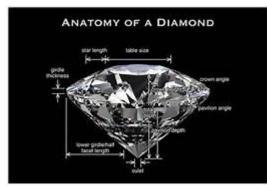
Fair

Diamonds in this category lack brightness, fire and scintillation.



Poor

Diamonds in this category show very little brightness, fire and scintillation.





	Unname d: 0	carat	cut	colo r	clarit Y	dept h	tabl e	pric e	x	у	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.9 5	3.9 8	2.4 3
1	2	0.21	Premiu m	E	SI1	59.8	61.0	326	3.8 9	3.8 4	2.3 1
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.0 5	4.0 7	2.3 1
3	4	0.29	Premiu m	1	VS2	62.4	58.0	334	4.2 0	4.2 3	2.6 3
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.3 4	4.3 5	2.7 5

	Unname d: 0	carat	cut	co r	olo cla y	rit de h	pt ta e	bl pr e	ic x	y z	
	carat	cut	color	clarit y	dept h	table	pric e	x	у	z	
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.9 8	2.4 3	
1	0.21	Premiu m	E	SI1	59.8	61.0	326	3.89	3.8 4	2.3 1	
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.0 7	2.3 1	
3	0.29	Premiu m	I	VS2	62.4	58.0	334	4.20	4.2 3	2.6 3	
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.3 5	2.7 5	

### (53940, 10)

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 53940 entries, 0 to 53939

Data columns (total 10 columns):

carat 53940 non-null float64

cut 53940 non-null object

color 53940 non-null object

clarity 53940 non-null object

depth 53940 non-null float64

table 53940 non-null float64

price 53940 non-null int64

x 53940 non-null float64

y 53940 non-null float64

z 53940 non-null float64

dtypes: float64(6), int64(1), object(3)

memory usage: 4.1+ MB

carat 0

cut 0

color 0

clarity 0

depth 0

table 0

price 0

x 0

y 0

z 0

dtype: int64

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5d54b59e8>

	carat	depth	table	price	x	У	Z
co un t	53940.00 0000	53940.00 0000	53940.0 00000	53940.00 0000	53940.0 00000	53940.000 000	53940.00 0000
me an	0.797940	61.74940 5	57.4571 84	3932.799 722	5.73115 7	5.734526	3.538734
std	0.474011	1.432621	2.23449 1	3989.439 738	1.12176 1	1.142135	0.705699
mi n	0.200000	43.00000 0	43.0000 00	326.0000 00	0.00000 0	0.000000	0.000000
25 %	0.400000	61.00000 0	56.0000 00	950.0000 00	4.71000 0	4.720000	2.910000

	carat	depth		table	e	price	x			у		Z	
50 %	0.700000	61.800 0	000	57.0 00	000	2401.000 000		5.70 0	000	5.710000		3.530000	
75 %	1.040000	62.500 0	000	59.0 00	000	5324.250 000		6.540 0	000	6.540000		4.040000	
ma x	5.010000	79.00000 0		95.0 00	000	18823.00 0000		10.7 00	400	58.900000	)	31 0	.80000
	carat	cut	colo	r	clari ty	depth	ta e	abl	pric e	x	у		Z
220 7	1.00	Premi um	G		SI2	59.1	5	9.	314 2	6.55	6.4 8	•	0.0
231 4	1.01	Premi um	Н		I1	58.1	5	9.	316 7	6.66	6.6 0	ì	0.0
479 1	1.10	Premi um	G		SI2	63.0	5	9.	369 6	6.50	6.4 7	•	0.0
547 1	1.01	Premi um	F		SI2	59.2	5	8.	383 7	6.50	6.4 7	•	0.0
101 67	1.50	Good	G		I1	64.0	6	51.	473 1	7.15	7.0 4	)	0.0
111 82	1.07	Ideal	F		SI2	61.6	5	6.	495 4	0.00	6.6 2	1	0.0
119 63	1.00	Very Good	Н		VS2	63.3	5	3.	513 9	0.00	0.0 0	)	0.0
136 01	1.15	Ideal	G		VS2	59.2	5	6.	556 4	6.88	6.8 3	;	0.0
159 51	1.14	Fair	G		VS1	57.5	6	57. I	638 1	0.00	0.0	)	0.0

	carat	depth	ı	tabl	е	price	x		у	Z	
243 94	2.18	Premi um	Н		SI2	59.4	61. 0	126 31	8.49	8.4 5	0.0
245 20	1.56	Ideal	G		VS2	62.2	54. 0	128 00	0.00	0.0	0.0
261 23	2.25	Premi um	I		SI1	61.3	58. 0	153 97	8.52	8.4 2	0.0
262 43	1.20	Premi um	D		VVS 1	62.1	59. 0	156 86	0.00	0.0	0.0
271 12	2.20	Premi um	Н		SI1	61.2	59. 0	172 65	8.42	8.3 7	0.0
274 29	2.25	Premi um	Н		SI2	62.8	59. 0	180 34	0.00	0.0	0.0
275 03	2.02	Premi um	Н		VS2	62.7	53. 0	182 07	8.02	7.9 5	0.0
277 39	2.80	Good	G		SI2	63.8	58. 0	187 88	8.90	8.8 5	0.0
495 56	0.71	Good	F		SI2	64.1	60. 0	213 0	0.00	0.0	0.0
495 57	0.71	Good	F		SI2	64.1	60. 0	213 0	0.00	0.0	0.0
515 06	1.12	Premi um	G		I1	60.4	59. 0	238 3	6.71	6.6 7	0.0

carat cut color clarity depth table price x y z

<seaborn.axisgrid.FacetGrid at 0x1e5c1374128>

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<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5c1392fd0>

<matplotlib.axessubplots.axessubplot 0x1e5d7e4ebe0="" at=""></matplotlib.axessubplots.axessubplot>
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1.4) Drop the 'Unnamed: 0' column as we already have Index.
Great, So there are no NaN values.
Wait
• Do you see the Min. Values of X, Y and Z. It can't be possible!!
• It doesn't make any sense to have either of Length or Width or Height to be zero

The Values are Distributed over a Small Scale.

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Let's Have a look at them.

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# Carat vs Price

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<seaborn.axisgrid.JointGrid at 0x1e5c1392c18>

<seaborn.axisgrid.FacetGrid at 0x1e5cbf2a6d8>

<seaborn.axisgrid.FacetGrid at 0x1e5be64e438>

<seaborn.axisgrid.FacetGrid at 0x1e5da6cad30>

<seaborn.axisgrid.FacetGrid at 0x1e5cbd87358>

<matplotlib.axes. subplots.AxesSubplot at 0x1e5dbf17828>

(array([3.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 2.0000e+00, 4.0000e+00, 1.1000e+01, 4.3000e+01, 2.1900e+02, 1.4240e+03, 5.0730e+03, 1.8242e+04, 2.2649e+04, 5.0330e+03, 8.5100e+02, 2.3400e+02, 8.7000e+01, 2.7000e+01, 1.1000e+01, 3.0000e+00, 1.0000e+00, 0.0000e+00, 0.0000e+00, 3.0000e+00]), array([43. , 44.44, 45.88, 47.32, 48.76, 50.2 , 51.64, 53.08, 54.52, 55.96, 57.4 , 58.84, 60.28, 61.72, 63.16, 64.6 , 66.04, 67.48, 68.92, 70.36, 71.8 , 73.24, 74.68, 76.12, 77.56, 79. ]),

## <a list of 25 Patch objects>)

<seaborn.axisgrid.JointGrid at 0x1e5af1e9eb8>

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5da5e4da0>

<seaborn.axisgrid.JointGrid at 0x1e5db6a7e80>

(2, 10)

	cara t	cut	colo r	clarit y	dept h	tabl e	pric e	x	У	Z	volume
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.9 5	3.9 8	2.4 3	38.20203 0
1	0.21	Premiu m	E	SI1	59.8	61.0	326	3.8 9	3.8 4	2.3 1	34.50585 6
2	0.23	Good	E	VS1	56.9	65.0	327	4.0 5	4.0 7	2.3 1	38.07688 5
3	0.29	Premiu m	I	VS2	62.4	58.0	334	4.2 0	4.2 3	2.6 3	46.72458 0
4	0.31	Good	J	SI2	63.3	58.0	335	4.3 4	4.3 5	2.7 5	51.91725 0
(0, !	50000)										

<seaborn.axisgrid.JointGrid at 0x1e5dce49668>

###### Linear Regression ######

Score: 0.8814

 $[0.87116164\ 0.88350756\ 0.87757769\ 0.87635168\ 0.88384912]$ 

MSE : 1911398.80

MAE : 926.72

RMSE: 1382.53

R2 : 0.88

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.0s finished

###### Lasso Regression ######

Score: 0.8659

[0.84325995 0.86900907 0.86386374 0.86539938 0.86976969]

MSE : 2162331.94

MAE : 909.60

RMSE: 1470.49

R2 : 0.87

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.1s finished

##### AdaBoost Regression ######

Score: 0.9093

[0.86364159 0.88625552 0.87610116 0.88472982 0.88632944]

MSE : 1462001.91

MAE : 827.10

RMSE: 1209.13

R2 : 0.91

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 17.9s finished

# ##### Ridge Regression #####

Score: 0.7537

 $[0.74232856\ 0.75599775\ 0.74753493\ 0.75626\quad 0.74960313]$ 

MSE : 3970442.17

MAE : 1346.18

RMSE: 1992.60

R2 : 0.75

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.0s finished

-	arane	i(u_lops=1)]: Doue	5 out of 5   elapsed	i: 0.08 finish
	Iter	Train Loss Rem	aining Time	
	1	14009477.5296	0.95s	
	2	12437807.7359	0.72s	
	3	11113339.5845	0.75s	
	4	9945244.2308	0.76s	
	5	8973416.9156	0.78s	
	6	8109014.7842	0.79s	
	7	7387120.0500	0.78s	
	8	6753937.9878	0.77s	
	9	6197182.6819	0.76s	
	10	5724689.0901	0.76s	
	20	3200362.4597	0.68s	
	30	2393542.3170	0.58s	
	40	2102586.3335	0.49s	
	50	1923964.9187	0.41s	

0.32s

60 1790574.6006

	4 600000 0006	0.04
70	1688380.2826	0.24s

80 1609829.0076 0.16s

90 1548089.0039 0.08s

100 1499127.4566 0.00s

Iter Train Loss Remaining Time

1 13994442.1962 0.40s

2 12429322.7982 0.39s

3 11112606.0983 0.66s

4 9944843.0686 0.71s

...

MSE : 1518030.06

MAE : 720.72

RMSE: 1232.08

R2 : 0.91

Output is truncated. View as a <u>scrollable element</u> or open in a <u>text editor</u>. Adjust cell output <u>settings</u>...

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 4.0s finished

#### ###### Random Forest ######

Score: 0.9809

[0.9782604 0.97855104 0.98081226 0.97523632 0.97956442]

MSE : 308285.07

MAE : 283.66

RMSE : 555.23

R2 : 0.98

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 9.9s finished

Score: 0.9822

R2 : 0.98

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 3.5s finished

## ##### KNeighbours Regression #####

Score: 0.9590

[0.95429058 0.95856983 0.95504994 0.94931403 0.95517559]

MSE : 660416.40

MAE : 424.98

RMSE: 812.66

R2 : 0.96

Score: 0.9590

R2 : 0.96

	Algorithms	R2-Scores
5	RandomForest Regression	0.982167
6	KNeighbours Regression	0.959033
2	AdaBoost Regression	0.909309
4	GradientBoosting Regression	0.905833
0	Linear Regression	0.881432
1	Lasso Regression	0.865866
3	Ridge Regression	0.753705

<sup>&</sup>lt;matplotlib.axes.\_subplots.AxesSubplot at 0x1e5af9edb70>

<sup>&</sup>lt;seaborn.axisgrid.FacetGrid at 0x1e5af98c780>

	Unname d: 0	carat		cut		co r	lo	cla y	rit	de h	pt	tal e	bl	pr e	ic	x		у	z
0	1	0.23		Ideal	I	Ε		SI2		61	.5	55	.0	32	6	3.9 5	)	3.9 8	2.4 3
1	2	0.21		Pren m	niu	Ε		SI1		59	.8	61	.0	32	6	3.8 9	3	3.8 4	2.3 1
2	3	0.23		Good	d	E		VS:	1	56	.9	65	.0	32	7	4.0 5	)	4.0 7	2.3 1
3	4	0.29		Prem m	niu	I		VS2	2	62	.4	58	.0	33	4	4.2 0	2	4.2 3	2.6 3
4	5	0.31		Good	d	J		SI2		63	.3	58	.0	33	5	4.3 4	3	4.3 5	2.7 5
	carat	cut	cole	or	clari y	it	de h	pt	tab	le	pri e	С	x		у		Z		
0	0.23	Ideal	E		SI2		61	.5	55.	0	326	6	3.9	95	3.9 8	)	2.4 3	1	
1	0.21	Premiu m	Ε		SI1		59	.8	61.	0	326	6	3.8	39	3.8 4	3	2.3 1	3	
2	0.23	Good	Ε		VS1		56	.9	65.	0	327	7	4.0	)5	4.0 7	)	2.3 1	3	
3	0.29	Premiu m	I		VS2		62	.4	58.	0	334	4	4.2	20	4.2 3	<u> </u>	2.6 3	5	
4	0.31	Good	J		SI2		63	.3	58.	0	33!	5	4.3	34	4.3 5	3	2.7 5	7	

(53940, 10)

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 53940 entries, 0 to 53939

Data columns (total 10 columns):

carat 53940 non-null float64

cut 53940 non-null object

color 53940 non-null object

clarity 53940 non-null object

depth 53940 non-null float64

table 53940 non-null float64

price 53940 non-null int64

x 53940 non-null float64

y 53940 non-null float64

z 53940 non-null float64

dtypes: float64(6), int64(1), object(3)

memory usage: 4.1+ MB

carat 0

cut 0

color 0

clarity 0

depth 0

0

table

price 0

x 0

y 0

z 0

dtype: int64

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5d54b59e8>

	carat	depth		table	e	price		x		у		Z	
co un t	53940.00 0000	53940 0000	.00	5394 0000		53940.00 0000		5394 0000		53940.000 000	)		3940.00 000
me an	0.797940	61.749 5	940	57.4 84	571	3932.799 722		5.73 7	115	5.734526		3.	538734
std	0.474011	1.4326	521	2.23449 1		3989.439 738		1.12 1	176	1.142135		0.	705699
mi n	0.200000	43.000 0	3.00000		000	326.0000 00	0.00		000	0.000000		0.	000000
25 %	0.400000	61.000 0	000	56.0 00	000	950.0000 00		4.71 0	000	4.720000		2.	910000
50 %	0.700000	61.800 0	61.80000 0		000	2401.000 000		5.70 0	000	5.710000		3.	530000
75 %	1.040000	62.500 0	000	59.0 00	000	5324.250 000		6.54 0	000	6.540000		4.	040000
ma x	5.010000	79.000 0	000	95.0000 00		18823.00 0000		10.7400 00		58.900000		31 0	1.80000
	carat	cut	colo	r	clari ty	depth		abl	pric e	x	у		z
220 7	1.00	Premi um	G		SI2	59.1		59. O	314 2	6.55	6. 8	4	0.0
231 4	1.01	Premi um	Н		I1	58.1		59. )	316 7	6.66	6. 0	6	0.0
479 1	1.10	Premi um	G		SI2	63.0		59. )	369 6	6.50	6. 7	4	0.0
547 1	1.01	Premi um	F		SI2	59.2		58. )	383 7	6.50	6. 7	4	0.0

	carat	depth	tab	le	price	x		у	z	
101 67	1.50	Good	G	l1	64.0	61. 0	473 1	7.15	7.0 4	0.0
111 82	1.07	Ideal	F	SI2	61.6	56. 0	495 4	0.00	6.6 2	0.0
119 63	1.00	Very Good	Н	VS2	63.3	53. 0	513 9	0.00	0.0	0.0
136 01	1.15	Ideal	G	VS2	59.2	56. 0	556 4	6.88	6.8	0.0
159 51	1.14	Fair	G	VS1	57.5	67. 0	638 1	0.00	0.0	0.0
243 94	2.18	Premi um	Н	SI2	59.4	61. 0	126 31	8.49	8.4 5	0.0
245 20	1.56	Ideal	G	VS2	62.2	54. 0	128 00	0.00	0.0	0.0
261 23	2.25	Premi um	I	SI1	61.3	58. 0	153 97	8.52	8.4 2	0.0
262 43	1.20	Premi um	D	VVS 1	62.1	59. 0	156 86	0.00	0.0	0.0
271 12	2.20	Premi um	Н	SI1	61.2	59. 0	172 65	8.42	8.3 7	0.0
274 29	2.25	Premi um	Н	SI2	62.8	59. 0	180 34	0.00	0.0	0.0
275 03	2.02	Premi um	Н	VS2	62.7	53. 0	182 07	8.02	7.9 5	0.0
277 39	2.80	Good	G	SI2	63.8	58. 0	187 88	8.90	8.8 5	0.0

	carat	depth	l	table	price	X		У	Z	
495 56	0.71	Good	F	SI2	64.1	60. 0	213 0	0.00	0.0	0.0
495 57	0.71	Good	F	SI2	64.1	60. 0	213 0	0.00	0.0	0.0
515 06	1.12	Premi um	G	I1	60.4	59. 0	238 3	6.71	6.6 7	0.0
20										

carat cut color clarity depth table price x y z
<seaborn.axisgrid.FacetGrid at 0x1e5c1374128>

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5c1392fd0>

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5d7e4ebe0>

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1.4) Dr	op the 'Unnamed: 0' column as we already have Index.
Great,	So there are no NaN values.
Wait	
•	Do you see the Min. Values of X, Y and Z. It can't be possible!!
•	It doesn't make any sense to have either of Length or Width or Height to be zero
Let's H	ave a look at them.
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The Va	lues are Distributed over a Small Scale.
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Carat v	s Price
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<seaborn.axisgrid.facetgrid 0x1e5cbf2a6d8="" at=""></seaborn.axisgrid.facetgrid>
<pre><seaborn.axisgrid.facetgrid 0x1e5be64e438="" at=""></seaborn.axisgrid.facetgrid></pre>
<pre><seaborn.axisgrid.facetgrid 0x1e5da6cad30="" at=""></seaborn.axisgrid.facetgrid></pre>

<seaborn.axisgrid.FacetGrid at 0x1e5cbd87358>

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<matplotlib.axes. subplots.AxesSubplot at 0x1e5dbf17828>
```

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(array([3.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 2.0000e+00, 4.0000e+00, 1.1000e+01, 4.3000e+01, 2.1900e+02, 1.4240e+03, 5.0730e+03, 1.8242e+04, 2.2649e+04, 5.0330e+03, 8.5100e+02, 2.3400e+02, 8.7000e+01, 2.7000e+01, 1.1000e+01, 3.0000e+00, 1.0000e+00, 0.0000e+00, 0.0000e+00, 3.0000e+00]), array([43. , 44.44, 45.88, 47.32, 48.76, 50.2 , 51.64, 53.08, 54.52, 55.96, 57.4 , 58.84, 60.28, 61.72, 63.16, 64.6 , 66.04, 67.48, 68.92, 70.36, 71.8 , 73.24, 74.68, 76.12, 77.56, 79. ]), <a list of 25 Patch objects>)
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<seaborn.axisgrid.JointGrid at 0x1e5af1e9eb8>

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5da5e4da0>

<seaborn.axisgrid.JointGrid at 0x1e5db6a7e80>

(2, 10)

	cara t	cut	colo r	clarit Y	dept h	tabl e	pric e	x	У	z	volume
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.9 5	3.9 8	2.4 3	38.20203 0
1	0.21	Premiu m	Е	SI1	59.8	61.0	326	3.8 9	3.8 4	2.3 1	34.50585 6
2	0.23	Good	E	VS1	56.9	65.0	327	4.0 5	4.0 7	2.3 1	38.07688 5
3	0.29	Premiu m	I	VS2	62.4	58.0	334	4.2 0	4.2 3	2.6 3	46.72458 0
4	0.31	Good	J	SI2	63.3	58.0	335	4.3 4	4.3 5	2.7 5	51.91725 0
(0, !	50000)										

<seaborn.axisgrid.JointGrid at 0x1e5dce49668>

## ###### Linear Regression ######

Score: 0.8814

 $[0.87116164\ 0.88350756\ 0.87757769\ 0.87635168\ 0.88384912]$ 

MSE : 1911398.80

MAE : 926.72

RMSE: 1382.53

R2 : 0.88

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.0s finished

##### Lasso Regression #####

Score: 0.8659

[0.84325995 0.86900907 0.86386374 0.86539938 0.86976969]

MSE : 2162331.94

MAE: 909.60

RMSE: 1470.49

R2 : 0.87

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.1s finished

###### AdaBoost Regression ######

Score: 0.9093

[0.86364159 0.88625552 0.87610116 0.88472982 0.88632944]

MSE : 1462001.91

MAE : 827.10

RMSE: 1209.13

R2 : 0.91

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 17.9s finished

##### Ridge Regression ######

Score: 0.7537

 $[0.74232856\ 0.75599775\ 0.74753493\ 0.75626\ 0.74960313]$ 

MSE : 3970442.17

MAE : 1346.18

RMSE: 1992.60

R2 : 0.75

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 0.0s finished

Iter	Train Loss	Remain	ing Time
1	14009477.52	96	0.95s
2	12437807.73	59	0.72s
3	11113339.58	45	0.75s
4	9945244.230	08	0.76s
5	8973416.915	56	0.78s
6	8109014.784	12	0.79s
7	7387120.050	00	0.78s
8	6753937.987	78	0.77s
9	6197182.682	19	0.76s
10	5724689.09	01	0.76s
20	3200362.45	97	0.68s
30	2393542.31	70	0.58s
40	2102586.33	35	0.49s
50	1923964.91	87	0.41s
60	1790574.60	06	0.32s
70	1688380.28	26	0.24s
80	1609829.00	76	0.16s
90	1548089.00	39	0.08s
100	1499127.4	566	0.00s
Iter	Train Loss	Remain	ing Time
1	13994442.19	62	0.40s
2	12429322.79	82	0.39s
3	11112606.09	83	0.66s
4	9944843.068	36	0.71s

• • •

MSE : 1518030.06

MAE : 720.72

RMSE: 1232.08

R2 : 0.91

Output is truncated. View as a <u>scrollable element</u> or open in a <u>text editor</u>. Adjust cell output <u>settings</u>...

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 4.0s finished

##### Random Forest #####

Score: 0.9809

[0.9782604 0.97855104 0.98081226 0.97523632 0.97956442]

MSE : 308285.07

MAE : 283.66

RMSE : 555.23

R2 : 0.98

[Parallel(n jobs=1)]: Done 5 out of 5 | elapsed: 9.9s finished

Score: 0.9822

R2 : 0.98

[Parallel(n\_jobs=1)]: Done 5 out of 5 | elapsed: 3.5s finished

##### KNeighbours Regression ######

Score: 0.9590

[0.95429058 0.95856983 0.95504994 0.94931403 0.95517559]

MSE : 660416.40

MAE : 424.98

RMSE: 812.66

R2 : 0.96

Score: 0.9590

### R2 : 0.96

	Algorithms	R2-Scores
5	RandomForest Regression	0.982167
6	KNeighbours Regression	0.959033
2	AdaBoost Regression	0.909309
4	GradientBoosting Regression	0.905833
0	Linear Regression	0.881432
1	Lasso Regression	0.865866
3	Ridge Regression	0.753705

<matplotlib.axes.\_subplots.AxesSubplot at 0x1e5af9edb70>

<sup>&</sup>lt;seaborn.axisgrid.FacetGrid at 0x1e5af98c780>